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Bayesian spatial filters for the extraction of source signals, a study in the peripheral nerve

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Abstract

The ability to extract physiological source signals to control various prosthetics offer tremendous therapeutic potential to improve the quality of life for patients suffering from motor disabilities. Regardless of the modality, recordings of physiological source signals are contaminated with noise and interference along with crosstalk between the sources. These impediments render the task of isolating potential physiological source signals for control difficult. In this paper, a novel Bayesian Source Filter for signal Extraction (BSFE) algorithm for extracting physiological source signals for control is presented. The BSFE algorithm is based on the source localization method *Champagne* and constructs spatial filters using Bayesian methods that simultaneously maximize the signal to noise ratio of the recovered source signal of interest while minimizing crosstalk interference between sources. When evaluated over peripheral nerve recordings obtained in-*vivo*, the algorithm achieved the highest signal to noise interference ratio ($>7.00\pm3.45\text{dB}$) amongst the group of methodologies compared with average correlation between the extracted source signal and the original source signal >0.93 . The results support the efficacy of the BSFE algorithm for extracting source signals from the peripheral nerve or as a pre-filtering stage for BCI methods.

Keywords

spatial filters; BCI; source localization; control; prosthetics

I. INTRODUCTION

Due to advances made in the field of robotics and functional neuro-prosthetics [1–4], research into the extraction of physiological source signals from human subjects to control prosthetic devices offer tremendous potential to improve the lives of patients suffering from physical disabilities. However, recordings of physiological source signals are often contaminated by both biological as well as electronic noise and interference along with crosstalk interference generated between the sources. As such, an algorithm that can separate each source signal both from the system noise and interference as well as other source signals is critical. To this end, we propose a Bayesian based spatial filter algorithm for the extraction of individual source signals (BSFE). The algorithm is based on the source

localization methodology *Champagne* [5, 6] and is designed to not only maximize the SNR of the individual source signals but also minimize the crosstalk between the source signals. To evaluate the algorithm, peripheral nerve electroneurography (ENG) was obtained using the Flat Interface Nerve Electrode (FINE) [7, 8] in an in-vivo preparation of the rabbit sciatic nerve.

Numerous manuscripts have been published focusing on several categories of control signals such as: (1) brain activity measured by electroencephalography (EEG) [9–13], electrocorticography (ECoG) [14–19] and magnetoencephalography (MEG) [20–24]; (2) peripheral nerve activity measured by ENG [25–29] and residual muscle activity measured by electromyography (EMG) [30–34]. Each of these modalities is accompanied with its own set of advantages and weaknesses. Measurements of brain activity offer potentially the greatest number of control signals. However, non-invasive methodologies such as EEG and MEG are limited by the quality of their recordings and can provide few degrees of freedom [35]. Invasive methods such as ECoG recordings deliver higher quality signals but greatly increase the risks related to the patients' health [36]. The physiological complexity of the brain also poses considerable challenges. While significant knowledge has been acquired regarding the brain, there is still no clear understanding of the exact process, pathways and mechanisms with which thoughts are turned into actions. As such, the generation and classification of a control signal and its intent is non-trivial and requires significant training of both the patient and the algorithm. In comparison, extracting control signals from EMG is less problematic. Most systems use non-invasive surface EMG and the relationship between the EMG control signal and the user's intent is relatively straightforward. However EMG is limited by the number of potential control signals it can provide and may be insufficient for more complex tasks. Peripheral nerve activity, on the other hand, offers several advantages over the other modalities: (a) multiple potential source signals are present within a peripheral nerve; (b) the functional anatomy of the peripheral nerves is known and is considerably more structured and simpler; (c) the physiological functions of the individual nerves are clearly understood, which facilitates the generation of controlled signals by human subjects and the classification of the intent by the algorithms; (d) the procedures are less invasive compared to ECoG and intracranial electrode placement surgeries but may offer superior source signals compared to surface EEG and EMG.

In the following sections, we will first present the details of the proposed algorithm, then the acute in-vivo experimental setup used to generate the biological source signals is explained, and finally the algorithm is implemented and evaluated with the experimentally recorded physiological signals.

II. Methods

In a realistic environment, source signals can be generated by directing a subject to perform a set number D_T of tasks while recordings of the peripheral nerve activity $Y_i \in \mathbb{R}^{K \times N}$, $i = 1: D_T$ are made during the performance of each task across K contacts over a period of N time points. Each Y_i can be modeled as a combination of the D_{S_i} number of source (fascicle) signals $S_i \in \mathbb{R}^N$ along with noises and interferences e

$$Y_i = \sum_{j=1}^{D_{S_i}} L_i^j S_i^j + e \quad (1)$$

$i=1:D_T$

where $L^j \in \mathbb{R}^K$ is the lead-field matrix that describes the sensitivity of the K electrode contacts to the particular source S^j with the assumption that the noise and interference within the system are the same across the various tasks. In the model described in (1), each set of $L_i S_i = \sum_{j=1}^{D_{S_i}} L_i^j S_i^j$ is a representation of the subjects' intent and can be used as potential control signals. To extract these signals, the proposed BSFE algorithm learns a set of spatial filters $F_i \in \mathbb{R}^K$ from Y_i such that when given a signal Y_{test} that contains a combination of control signals $L_i S_i$ along with noise and interference e

$$Y_{test} = \sum_{i=1}^{D_T} L_i S_i + e \quad (2)$$

$i=1:D_T$

the output of each spatial filter F_i is approximately

$$F_i Y_{test} \approx \sum_{j=1}^{D_{S_i}} S_i^j \quad (3)$$

$i=1:D_T$

Therefore each spatial filter must accurately extract the corresponding source signals for each control task while minimizing the system noise and interference as well as cross-talk from other source signals.

II. A Learning of the Spatial Filters

The proposed BSFE algorithm is a modification of the *Champagne* algorithm that emphasizes source signal extraction over source localization. The *Champagne* algorithm models the recorded peripheral nerve signal Y_i in (1) as a combination of pixel source activity $\tilde{S}_i$ and noise plus interference e

$$Y_i = \tilde{L} \tilde{S}_i + e \quad (4)$$

where $\tilde{S} \in \mathbb{R}^{M \times N}$ are the N time point activity of the M pixels within the cross section of the finite element model of the FINE. In this model, each pixel is treated as a potential source that can influence the voltages recorded by the K FINE contacts via the relationship described by the pixels' lead-field matrix $\tilde{L} \in \mathbb{R}^{K \times M}$. The lead-field matrix was constructed according to the methods described in [37]. Briefly, a rectangular finite element model of the FINE positioned over an empty epineurium enclosing a homogeneous volume conductor was created shown in fig. 1a. The FINE measured 5mm by 1.5mm and contained 16 contacts with contacts 1 to 8 arranged from the top left to the top right corner while contacts 9 to 16 were arranged from the bottom left to the bottom right corner. In the finite element

model, the cross section of the FINE was divided into 26 by 11 pixels, which leads to $M = 286$ possible source locations. The sensitivity of contacts (1, 6, 11 and 16) to these pixels is plotted in fig. 1b.

The location of the sources present in the recordings are determined by estimating which of the 286 pixel locations contains an actual physiological source, to this end, *Champagne* introduces the following likelihood model based on (4)

$$p(Y_i|\tilde{S}_i) \propto \exp \left(-\frac{1}{2} \|Y_i - \tilde{L}\tilde{S}_i\|_{C_e}^2 \right) \quad (5)$$

$i=1:D_T$

where $\|Q\|_C = \sqrt{\text{trace}[Q^T C^{-1} Q]}$. $C_e \in \mathbb{R}^{K \times K}$ is an unknown covariance matrix that describes the noise plus interference in the system and is computed according to [5]. The individual sources $\tilde{S}_{i,j}$, $j = 1:M$ are modeled as independent zero mean Gaussian distributions with each $\tilde{S}_{i,j}$ having covariance $C_{\tilde{S}_{i,j}}$

$$p(\tilde{S}_{i,j}^n) = \mathcal{N}(\tilde{S}_{i,j}^n | 0, C_{\tilde{S}_{i,j}}) \quad (6)$$

$i=1:D_T$

where $n = 1:N$. *Champagne* also makes the assumption that the sources are independent in time, leading to the source prior

$$p(\tilde{S}_i | C_{\tilde{S}_i}) \propto \exp \left(-\frac{1}{2} \text{trace} \left[\tilde{S}_i^T C_{\tilde{S}_i}^{-1} \tilde{S}_i \right] \right) \quad (7)$$

$i=1:D_T$

where $C_{\tilde{S}_i}$ is a diagonal matrix with the covariance for each pixel located along the diagonal. With this model, the approximation of $C_{\tilde{S}_i}$ infers the pixel locations where the sources most likely reside, with increasing values of $C_{\tilde{S}_i}$ leading to higher probabilities that a source exist at the corresponding pixel and pixels that are not learned sources have $C_{\tilde{S}_i}$ values approaching zero. To learn $C_{\tilde{S}_i}$ from Y_i , *Champagne* minimizes the log-likelihood function $\mathcal{L}(Y_i | C_{\tilde{S}_i})$ with respect to $C_{\tilde{S}_i}$ given by

$$\mathcal{L}(Y_i | C_{\tilde{S}_i}) = -2 \log(p(Y_i | C_{\tilde{S}_i})) = -2 \log \left(\int p(Y_i | \tilde{S}_i) p(\tilde{S}_i | C_{\tilde{S}_i}) d\tilde{S}_i \right) \quad (8)$$

$i=1:D_T$

which leads to the minimization of the following cost function

$$\mathcal{L}(Y_i | C_{\tilde{S}_i}) \triangleq \text{trace} [C_{Y_i} C_{E_i}^{-1}] + \log(|C_{E_i}|)$$

$C_{E_i} = C_e + \tilde{L} C_{\tilde{S}_i} \tilde{L}^T$ and $C_{Y_i} = N^{-1} Y_i Y_i^T$ (9)

$i=1:D_T$

Once $C_{\tilde{S}_i}$ is determined, spatial filters F_i for each control task can be constructed as

$$F_i = C_{\tilde{s}_i} \tilde{L}^T (C_e + \tilde{L} C_{\tilde{s}_i} \tilde{L}^T)^{-1} \quad i=1:D_T \quad (10)$$

One final piece of the puzzle left is the approximation of C_e the covariance matrix that describes the noise and interference in the system. The procedure for the determination of C_e is described in [5]. Briefly, the nerve recordings Y_i for each control task are modeled as a mixture of source signals $X_i \in \mathbb{R}^{D_X \times N}$, interference signals $U_i \in \mathbb{R}^{D_U \times N}$ and random noise $V \in \mathbb{R}^{K \times N}$.

$$Y_i = A_i X_i + B U_i + V \quad i=1:D_T \quad (11)$$

D_X and D_U are the number of source and interference signals to be approximated respectively. The source and interference signals are assumed to be independent Gaussian distributions with zero mean and unit precision. The random noise term V is described by a diagonal precision matrix C_V . Again we assumed the same noise and interference are present during the performance of each control task. Given an initial choice of the number of source and interference signals to be learned, the algorithm utilizes variational Bayes expectation maximization to learn the set of model parameters that best fit the data covariance matrix C_{Y_i} by

$$C_{Y_i} \approx A_i A_i^T + B B^T + C_V^{-1} \quad (12)$$

where the learned interference and noise parameters are used to compute C_e .

$$C_e = B B^T + C_V^{-1} \quad (13)$$

With the approximation of C_e complete, C_{S_i} can be learned by minimizing (9) and spatial filters can then be constructed according to (10).

Looking at the *Champagne* algorithm from a source signal extraction perspective instead of source localization, it can be shown that its method of spatial filter construction tends to increase the SNR of the extracted source signals. Looking at the cost function in (9), while the solution cannot be obtained analytically, the final solution C_{S_i} learned through optimization should approximate the following condition:

$$\frac{\partial \mathcal{L}(Y_i | C_{\tilde{s}_i})}{\partial C_{\tilde{s}_i}} = -C_{Y_i} (C_e + \tilde{L} C_{\tilde{s}_i} \tilde{L}^T)^{-1} L^T L (C_e + \tilde{L} C_{\tilde{s}_i} \tilde{L}^T)^{-1} + (C_e + \tilde{L} C_{\tilde{s}_i} \tilde{L}^T)^{-1} L^T L = 0 \quad (14)$$

leading to

$$\tilde{L} C_{\tilde{s}_i} \tilde{L}^T \approx C_{Y_i} - C_e \quad (15)$$

from which it can be observed that C_{S_i} values learned for the various pixel locations are directly proportional to $C_{Y_i} - C_e$ where electrode contacts with large recordings C_{Y_i} , ideally from source signals of interest, and small noise plus interference C_e result in higher C_{S_i} values for pixels that fall under their influence while electrode contacts that record mostly noise, i.e. $C_{Y_i} - C_e \rightarrow 0$, have little influence on pixel C_{S_i} values. With this in mind, we now examine (10) the equation for the constructing the spatial filters once C_{S_i} and C_e are learned. It can be observed from the equation that the filter weight magnitude for each electrode contact asymptotically increases for higher pixel C_{S_i} values which themselves are proportional to $C_{Y_i} - C_e$. Thus electrode contacts with stronger signals relative to background noise and interference will have higher filter coefficients which tends to increase the SNR of the filtered output. Taking advantage of this property, we modified the definition of C_e to include the covariance matrices of the interfering sources effectively thereby treating sources that are not the target of interest for the current spatial filter as interference. So for each set of source signals Y_i , $i = 1: D_X$, we replace the definition in (13) with the following

$$\begin{aligned}
 C_{e,i} &= BB^T + C_v^{-1} + CT_i \\
 (CT_i)_{k,l} &= \max \left(\left(A_j A_j^T \right)_{k,l} \right) \text{ for } j=1:D_T, j \neq i \\
 &\quad \text{or} \\
 CT_i &= \sum_{\substack{j=1, j \neq i \\ k, l=1:K}}^{D_T} A_j A_j^T
 \end{aligned} \tag{16}$$

The two possible definitions for CT_i are problem-dependent. If the interfering source activity do not overlap in time then the first definition should be used. However if the interfering source activity do overlap in time then the second definition should be used. By incorporating $C_{e,i}$ instead of C_e , equation (15) becomes

$$\tilde{L} C_{\tilde{S}_i} \tilde{L}^T \approx C_{Y_i} - C_{e,i} \tag{17}$$

And equation (10) becomes

$$F_i = C_{\tilde{S}_i} \tilde{L}^T (C_{e,i} + \tilde{L} C_{\tilde{S}_i} \tilde{L}^T)^{-1} \tag{18}$$

This method (BSFE) results in spatial filters that not only minimize the system noise and interference but also the crosstalk interference between the source signals.

II. B Control Signal Generation and Data Collection

Acute peripheral nerve activity were induced and recorded from New Zealand White Rabbits as illustrated in fig. 2. The rabbits were anesthetized with 20–50 mg/kg IM ketamine and 5 mg/kg IV diazepam and maintained with 60 mg/kg IV alpha-chloralose (followed by one quarter dose every 2 hours or as needed) and .02 mg/kg IM buprenex. All protocols

were approved by the Case Western Reserve University IACUC. Recordings were made from a novel 16-channel tripolar FINE placed on the sciatic trunk near the popliteal fossa. The FINE offers improved recording selectivity by reshaping the geometry of the nerve without inducing damage [7, 8]. The recorded peripheral nerve signals were AC coupled, amplified, multiplexed and low-pass filtered at 5 kHz by an RHA1016 preamplifier chip (Intan Technologies, Utah). A National Instruments data acquisition card was used to perform A-to-D conversion and sampling at 15 kHz/channel. Tripolar stimulation FINEs were placed on the Tibial and Peroneal branches of the Sciatic nerve, distal to the recording cuff. The Tibial and Peroneal branch each represent a potential source signal, $D_T = 2$ and neural activity were induced within each branch using two separate stimulation methods. With the first method, 130Hz sinusoidal stimulations lasting approximately 30s with peak to peak amplitude of 600 μ A were separately delivered to each individual nerve branch to generate source activity in the form of compound action potentials (CAPs). Spatial filters were then constructed for each nerve using their individually recorded signals. With the second methods, 5kHz sinusoidal stimulations lasting approximately 4s in duration with peak to peak amplitude of 600 μ A were delivered first to the Peroneal branch than a second identical stimulation is delivered to the Tibial branch 2s following the Peroneal stimulation onset. This resulted in recordings consisting of 2s of individual branch activity along with 2s when both branches were activated. The individual branch activity was used to construct the corresponding spatial filters. In all cases, sinusoidal stimulations were used to facilitate artifact removal. The recorded signals were post-processed using an 800Hz – 3kHz band-pass filter in order to reduce any non-essential EMG and stimulation artifacts.

II. C Training and Evaluation

The BSFE algorithm requires an initial selection of the number of source and interference signals to be approximated in (11) which were both set to $D_X = D_U = 15$. The algorithm was evaluated over both the CAP trains elicited via individual 130Hz sinusoidal stimulations of the Peroneal/Tibial branches and the pseudo-random neural activity induced with 5kHz sinusoidal stimulations of the Peroneal/Tibial branches. The performance of the resultant BSFE spatial filters were compared against spatial filters constructed from the traditional *Champagne* algorithm, the SBF algorithm presented in [38] and the reference signal which was computed as the average signal across all the contacts. For every trial, 30% of the data were used for training the algorithms while the remaining 70% for testing.

The following parameters were used to evaluate the performance of the filter outputs over the 130Hz CAP dataset: signal to noise plus interference ratio (SNIR); signal to noise ratio (SNR); signal to crosstalk ratio (SCTR); SNIR gain (SNIRG); SNR gain (SNRG) and SCTR gain (SCTRG).

1.
$$SNIR = \frac{P(ACAP_{interest})}{P(Noise) + P(ACAP_{interference})}$$
2.
$$SNR = \frac{P(ACAP_{interest})}{P(Noise)}$$
3.
$$SCTR = \frac{P(ACAP_{interest})}{P(ACAP_{interference})}$$

$$4. \quad SNIRG = \frac{SNIR}{SNIR_{reference}}$$

$$5. \quad SNRG = \frac{SNR}{SNR_{reference}}$$

$$6. \quad SCTR G = \frac{SCTR}{SCTR_{reference}}$$

where

$$P(X) = \frac{1}{n} \sum_{i=1}^n X_i^2$$

Noise and interference parameters were estimated from segments of background recordings devoid of source activity. $ACAP_{interest}$ and $ACAP_{interference}$ were the averaged CAP waveforms for the filtered source of interest and the interference source respectively. The averaging was done to remove most of the noise components and isolate each source's CAP waveform and its power. This was possible because the stimulation was periodic. The reference signals were obtained by averaging all the contacts together.

For the 5kHz generated pseudo-random ENG dataset, the comparisons between the algorithms focus mainly on the SNIR, and SNIRG obtained with each filter. The definition of SNIRG remains the same as above while the SNIR values are computed as

$$1. \quad SNIR = \frac{P(Y_{interest})}{P(Y_{interference})}$$

where $Y_{interest}$ and $Y_{interference}$ were recordings during periods where the source of interest and the interference source were individually activated.

Finally for each set of performance comparisons, one-way ANOVA was used to test for significant differences within each group with $p < 0.05$ being significant. If significant differences existed, pairwise post-hoc Tukey-Kramer comparisons were performed for the entire group.

III. RESULTS

III. A Evaluation over the 130Hz CAP Trains

A total of N=12 signal trials each one consisting of 10s of recorded background activity followed by 30s of individual 130Hz sinusoidal stimulation of the Peroneal and Tibial branch respectively were performed across six animals. In fig. 3, the recorded CAPs elicited from individual stimulations of the Peroneal and Tibial branches are plotted. The signals are obtained by averaging the recordings across the 16 FINE electrode contacts and represent the reference signals. For each trial, spatial filters for extracting the individual Peroneal and Tibial source signals were built separately with the BSFE, *Champagne* and SBF algorithms using 30% of the data and then tested on the remaining 70% of the data. The performance of the spatial filters was then evaluated according to the measures detailed in the methods section.

In fig. 4, three reference test signals are plotted along with their filtered outputs obtained with the BSFE, *Champagne* and SBF algorithms. The three test signals were constructed by concatenating 100ms segments of Peroneal and Tibial source activity. The Peroneal and Tibial spatial filter outputs are presented on the left and right side of the figure respectively. The exact period when each source is active is demarcated by the dashed lines. It is the objective of the Peroneal and Tibial spatial filters to extract their corresponding source signals from the test signal while minimizing noise, interference and crosstalk. The first reference test signal contains Peroneal and Tibial CAPs that are similar in amplitude as shown in the top plots of fig. 4a. By simply averaging across the contacts it is impossible to isolate each individual signal. In the next row of plots, the SBF based Tibial filter is able to reject significant portions of the Peroneal activity, but its Peroneal filter output still contains substantial Tibial activity. The *Champagne* based spatial filters, shown in the third row, do not exhibit improvements in crosstalk rejection over the reference signals. However this was expected since *Champagne* was designed to approximate the location of the sources only. BSFE outputs, illustrated in the last row, present a different picture. Both the BSFE based Peroneal and Tibial filters demonstrate considerable improvement in crosstalk rejection where the Peroneal filter output contains very little Tibial activity and vice versa. In fig. 4b and 4c, the second and third reference test signals are plotted along with their filtered outputs. For these signals, the elicited CAPs from one source (Tibial then Peroneal) are significantly larger in amplitude compared to the other (Peroneal then Tibial). In both situations the BSFE based filters achieved the best results and was able to extract both the stronger and weaker source signals with minimum noise, interference plus crosstalk.

In fig. 5, the mean and standard deviation of the SNIRG, SNRG and SCTRГ achieved across N=12 trials, using the various algorithms are plotted for both the Peroneal and Tibial source signals. Examination of the SNRGs, shown in fig. 5a–5b, reveals significant differences exist within the Peroneal spatial filters $F(3,36) = 8.44, p < 0.001$ with BSFE achieving the lowest SNRG ($42.20 \pm 27.05\%$) relative to the reference, $p < 0.001$. For the Tibial source signal, there was no significant differences between the SNRGs within the group, $F(3,36) = 2.54, p = 0.072$. A different picture is presented for the SNIRGs achieved with the various algorithm illustrated in fig. 5c–5d. For both the Peroneal and Tibial source signals, BSFE presents significantly higher SNIRG when compared to the rest of the group with SNIRG of ($20.66 \pm 6.84\text{dB}$), $F(3,36) = 28.53, p < 0.001$ for the Peroneal spatial filters and SNIRG of ($24.99 \pm 8.27\text{dB}$), $F(3,36) = 58.36, p < 0.001$ for the Tibial spatial filters. These results demonstrate that while the BSFE algorithm sacrifices some SNR, it can achieve a much higher SNIR by rejecting cross-talk from interfering sources. This point is further demonstrated in fig. 5e and 5f. In the plots, the SCTRГs obtained with each algorithm are plotted for both the Peroneal and Tibial signals. The SCTRГ comparisons mirror that of the SNIRG comparisons with BSFE achieving significantly higher SCTRГ for both signal branches, $p < 0.001$. This further indicates that the gains in SNIR by BSFE are driven mainly by improving the source signal strength relative to crosstalk interference. These results were expected since the elicited CAPs were much higher in power compared to the background noise and interference.

In fig. 6, the accuracy of the filtered Peroneal and Tibial CAP waveforms are evaluated by comparing them to the reference CAP waveforms. Examples of the reference Peroneal and Tibial CAPs for a single trial are plotted in fig. 6a along with the same CAPs obtained through the BSFE filters. The displayed CAP waveforms are obtained by averaging 1300 CAPs together and normalized to unit variance. As expected, the Peroneal BSFE filter was able to accurately extract the Peroneal CAP waveform while rejecting the Tibial CAP. Vice versa, the Tibial BSFE filter was able to extract the Tibial CAP waveform faithfully while eliminating the Peroneal CAP waveform. In fig. 6b, the mean and standard deviation of the Pearson's correlation coefficient (R) between the averaged reference Peroneal and Tibial CAPs and the averaged filtered Peroneal and Tibial CAPs are plotted separately for both the Peroneal and Tibial filters built using SBF, *Champagne* and BSFE. With each filter set, the averaged filtered CAP waveform for the source of interest should exhibit high correlations with its averaged reference CAP waveform while the averaged filtered interference source CAP should be rejected and thus exhibit less correlation with its averaged reference waveform. Looking at the Peroneal filters' performance, each algorithm was able to accurately recover the Peroneal CAP waveform with mean $R_{\text{Peroneal}} > 0.94$. However only the BSFE based Peroneal filters were able to reject the Tibial CAP waveforms, $R_{\text{Tibial}} = 0.15 \pm 0.081$, a significant improvement over the remaining algorithms $F(3,36) = 84.72$, $p < 0.001$. Analysis of the Tibial filters yielded similar results. Again the different algorithms were all able to recover the waveforms of the source of interest with accuracy $R_{\text{Tibial}} > 0.93$. However only the BSFE based Tibial filters were able to significantly reject the Peroneal CAP waveforms $R_{\text{Peroneal}} = 0.19 \pm 0.21$, $F(3,36) = 63.92$, $p < 0.001$. These results along with the previous evaluation of the SNR, SCTR and SNIR demonstrate the efficacy of the BSFE filters to extract the source signal of interest with high accuracy while minimizing not only the noises and interferences within the environment but also cross-talk interferences from other sources.

III. B Evaluation over the 5kHz induced pseudo-spontaneous peripheral nerve activity

To further evaluate the performance of BSFE, we generated sets of pseudo-random peripheral nerve activity with 5kHz sinusoidal stimulations with the stimulation artifacts removed through filtering [26]. These signals are physiologically more realistic when compared to the 130Hz stimulation protocol. An example of the average ENG recording across the sixteen contacts for a single 5kHz stimulation trial is shown in the top plot of fig. 7a. The signal is representative of all the trials and consists of a background period (B) absent of any stimulation, then a period of Peroneal stimulation (P) followed by a period of both Peroneal and Tibial stimulation (P+T) and finally ending with a period of Tibial only stimulation (T). Note at the beginning of each stimulation onset, stimulation artifacts are present and marked by the arrows in the figure. The second plot of fig. 7a shows the 0.1s running average of the reference signal power. Because the reference signal was constructed by simply averaging the sixteen contacts together, the Peroneal and Tibial signal powers were both present resulting in the largest signal powers occurring during the (P+T) period when both branches were stimulated. BSFE spatial filters were constructed for both the Peroneal and Tibial sources and the running average of their output signal powers are displayed in the two subsequent plots. In the example, both the BSFE Peroneal and Tibial filters were able to extract their source of interest with stable signal powers while rejecting

the interfering source. During the middle (P+T) phase, there are no visible increases in signal power due to the activation of the interfering source from each output and both filters were able to eliminate the high powered stimulation artifacts generated from their respective interfering source. In fig. 7b the SNIRG achieved for the Peroneal and Tibial source signals with BSFE are compared with the reference signal, SBF and *Champagne*. For the Peroneal filter comparison, one-way ANOVA found significant differences within the group $F(3,72) = 40.01$, $p < 0.001$ and the BSFE based Peroneal filters achieved significantly higher SNIRG ($6.56 \pm 1.75\text{dB}$) when compared to the remaining methods $p < 0.001$. Similar results were also found with the comparison of the Tibial filters where again BSFE achieved the highest SNIRG performance ($7.31 \pm 3.43\text{dB}$) amongst the various algorithms, $F(3,72) = 50.93$, $p < 0.001$.

To further evaluate the performance of the BSFE filters on the pseudo-random dataset, the linearity of the signal power is quantified during the period of P to P+T for the Peroneal filters and P+T to T period for the Tibial filters. An effective spatial filter should reject any sudden change in signal power due to the activation of the interfering source and maintain a linear trajectory while an ineffective filter would result in step response like changes in signal power upon the activation of the interfering source. Illustrated in fig. 8a, linear regression minimizing the least square error was performed over the data segments (I, II) and (II, III). The data segments were selected to avoid the stimulation artifacts. For the linear regression results, spatial filters with superior crosstalk rejection should yield lower root mean square error (RMSE) as demonstrated by the linear regression comparison between the reference signal and the BSFE filtered signals. In order to account for the differences in magnitude between the trials, the RMSE values for the Peroneal filters were normalized to the signal power of data segment I while the RMSE values of the Tibial filters were normalized to the signal power of data segment III. In fig. 8b the mean and standard deviation of the ratio between the normalized RMSE achieved with the various algorithms and the reference signal across the N=19 trials are plotted for the Peroneal and Tibial filters. During the Peroneal filter comparisons, one-way ANOVA pointed to significant differences within the group $F(3,72) = 6.22$, $p < 0.001$ with BSFE achieving the lowest RMSE ($25.86 \pm 14.94\%$), $p < 0.001$. Similar results were also obtained with the Tibial filter comparisons with BSFE obtaining the lowest RMSE ($28.09 \pm 17.33\%$) within the group $F(3,72) = 73.29$, $p < 0.001$. These results along with the previous analysis demonstrate the improvement in performance with the BSFE algorithm relative to the reference signal, *Champagne* and the SBF algorithm. In table 1, a summary of the mean and standard deviation of the absolute SNIR values achieved with each algorithm for the Peroneal and Tibial source signals using both the 130Hz and 5kHz experimental protocols is presented. In accordance with previous results, the BSFE based spatial filters achieved the best SNIRs for all situations.

IV. DISCUSSION

In this paper, we present a novel algorithm BSFE to extract physiological source signals for the purpose of controlling neuro-prosthetics. Based on the source localization algorithm *Champagne*[5, 6], BSFE constructs spatial filters that maximize the SNIR of the extracted

source signals by taking account of not only the noise and interference within the system but also crosstalk interference from other sources of interest.

To establish the efficacy of BSFE, its performance is evaluated against the reference signal, the original *Champagne* algorithm and the SBF algorithm using a common dataset. The dataset consists of acute ENG recordings from the dog sciatic nerve that are generated by the individual activation of the Tibial and Peroneal branches using both 130Hz and 5kHz sinusoidal stimulations. Because the reference signal and *Champagne* are not designed to extract source signals, we expected the BSFE to achieve higher SNIR relative to these methodologies. However the SBF algorithm is a source signal extraction algorithm that is designed to achieve high SNIR and have demonstrated its efficacy [38]. For both the comparisons over the 130Hz CAP train dataset and the 5kHz pseudo-random ENG dataset, BSFE achieved the highest SNIR amongst the different algorithms, including SBF, while maintaining accurate reconstruction of the source signal waveforms. The significant increases in SNIR achieved with the BSFE spatial filters provide significant advantages in utilizing the source signals they extract for control and because the relationship between the control task and the recorded ENG activity is well understood, these extracted source signals can be directly used to implement various control schemes without additional processing and the high SNIR will allow for different levels or gradients of control. If however, the control task and the recorded ENG share a more complicated relationship, then the extracted signals can be used as inputs for a regression algorithm the output of which can be used to for various control tasks.

While this study utilizes ENG recordings to demonstrate the efficacy of BSFE, the proposed algorithm can also be used in BCI applications. Similar to the methods of common spatial patterns (CSP) [39–42], BSFE constructs spatial filters that try to maximize the discriminative information between different control tasks, described by the SNIRs. The algorithm can be implemented for multiple classes or control tasks using (16) to isolate the contacts that contain information most relevant to the current control task of interest in an attempt to improve the performance of the classifiers.

In this study, the datasets used to evaluate the BSFE algorithm were collected in acute in-vivo preparations. The stimulated ENG exhibited high SNR that may be contrary to realistic physiological conditions. As such, chronic experiments in animals are the next step where actual peripheral nerve activity can be recorded using implanted FINEs along with the necessary data acquisition hardware. The proposed BSFE algorithm can then be tested within a physiologically accurate environment. The performance of BSFE in a multiple sources environment also requires further analysis since future applications in human patients will require the source signal extraction algorithm to be effective in isolating individual signals from higher number of sources whereas only two sources (Peroneal and Tibial) exist in the datasets used for this study. This can be accomplished by using computational models of the peripheral nerve [43]. In conclusion, we present a novel algorithm BSFE based on the source localization algorithm *Champagne*. The algorithm is able to achieve the best SNIR in a group comparison with other algorithms and can be used to extract source signals for control tasks.

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Figure 1.

(a) Finite element model of the 16 contacts FINE electrode placed around an empty epineurium encasing a homogeneous volume conductor. The model was used to generate the lead field matrix. (b) Sensitivity plots of four selected contacts.

Figure 2.
Experimental setup of the stimulation and recording electrodes.

Figure 1.
Examples of the CAP trains generated by the 130Hz sinusoidal stimulation protocol for both the Peroneal and Tibial sources.

Figure 2.

Illustration of the reference test signals along with the Peroneal and Tibial filter outputs for SBF, *Champagne*, and BSFE. (a) Reference test signal consisting of Peroneal and Tibial activity with similar amplitudes. (b) Reference test signal containing Tibial CAPs that were considerably stronger than the Peroneal CAPs. (c) Reference test signal containing Peroneal CAPs that were significantly larger than Tibial CAPs. It can be observed that in all three cases, only the BSFE spatial filters is able to extract the source signal of interest while significantly rejecting the interfering source.

Figure 3.

Performance comparison between the various algorithms for both the Peroneal and Tibial sources. The BSFE based spatial filters achieved the highest SNIRG for both sources. The significant improvement in SNIRG achieved with the BSFE algorithm can be attributed to its superior crosstalk rejection capability as demonstrated by the similar results observed in the SCTR comparisons.

Figure 4.

Evaluation of the signal recovery accuracy for each algorithm. (a) Examples of the averaged reference Peroneal and Tibial CAP waveforms are plotted along with the BSFE filtered CAP waveforms for both the Peroneal and Tibial filters. For each filter, the CAP waveform is accurately constructed for the source of interest while the CAP for the interfering source demonstrates significantly diminished correlation with their reference waveform. (b) Comparison of the correlation coefficient achieved with the various algorithms for both the Peroneal and Tibial filters. Each algorithm is able to recover the source signal of interest's waveform accurately. However only the BSFE algorithm is able to reject the interfering source's waveform.

Figure 5.

(a) An example of the 5kHz stimulation generated pseudo-random reference signal along with the normalized 0.1s signal power running average for the reference signal and the BSFE based Peroneal and Tibial spatial filter outputs. The signals consist a period of background activity (B) then a period of Peroneal stimulation (P) followed by a period of simultaneous Peroneal and Tibial stimulation (P+T) and ends with a period of Tibial stimulation (T). The relatively linear trajectories of the normalized power running average between the periods P to P+T for the Peroneal spatial filter and P+T to T for the Tibial spatial filter demonstrate the crosstalk interference rejection achieved with the BSFE

algorithm. Note the strong stimulation artifacts seen in the reference signal and marked by the arrows are also significantly reduced by the BSFE spatial filters. (b) The SNIRG performance comparison between the various algorithms for both the Peroneal and Tibial sources. Again BSFE based spatial filters achieved the best performance.

Figure 6.

Evaluation of the linearity of the normalized signal power running average trajectory for the recovered Peroneal and Tibial source signals during the periods P to P+T and P+T to T respectively. (a) Linear regression is performed using data segments I and II for the Peroneal BSFE filter outputs and data segments II and III for the Tibial BSFE filter outputs. The data segments I, II and III are marked to avoid the stimulation artifacts. When compared to the same linear regression performed on the reference signal, linear regression on the BSFE filter output presents significantly less RMSE due to the crosstalk rejection achieved with the BSFE spatial filters that eliminates the changes in signal power when the interference source is activated/deactivated. (b) Comparison of the RMSE normalized to the signal of interest's power. BSFE spatial filters achieved the lowest normalized RMSE.

Table 1

Final SNIR achieved with the various algorithms for both the 130Hz CAP train dataset and the 5kHz generated pseudo-random ENG dataset. The BSFE based spatial filters achieved the highest SNIR in all situations.

Algorithms				
	Input	SBF	Champagne	BSFE
SNIR (130Hz) (dB)	Peroneal	0.61±9.17	4.61±10.71	0.85±8.80
	Tibial	-0.61±9.17	7.61±9.18	-0.29±9.05
SNIR (5k) (dB)	Peroneal	0.45±4.32	1.71±5.26	0.64±4.32
	Tibial	-0.45±4.32	2.65±4.19	-0.46±4.31